Konya Mühendislik Bilimleri Dergisi, c.14, s.3, 1896-1915, 2026
Konya Journal of Engineering Sciences, v.14, n.3, 1896-1915, 2026
ISSN: 2667-8055 (Electronic)
DOI: 10.36306/konjes.1727780

INVESTIGATION of PHYSICAL RISK FACTORS in NATURAL STONE QUARRIES and ESTIMATION of PM CONCENTRATIONS with M5P DECISION TREE

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Highlights

- Evaluation of physical risk factors such as noise, vibration and particulate matter (PM) in a natural stone quarry with a different risk method
- Using the M5P decision tree algorithm for PM concentrations
- PM measurement in monolamella and daimond wire cutting machines
- PM concentration prediction for monolamella and diamond wire cutting machine by decision tree approach

Graphical Abstract



Figure PM and noise measurement in natural stone monolamella and wire cutting machines (a; Monolamella machine b; diamond wire cutting machine)

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(Received: 26.06.2025; Accepted in Revised Form: 08.03.2026)

ABSTRACT: In this study, particulate matter (PM) concentrations (TSP, PM_{10}, $PM_{2.5}$, and PM_1), as well as noise and ground vibrations, were measured and evaluated during monolamella and diamond wire cutting operations in two travertine quarries in Sivas province. PM concentrations released during the monolamella process exhibited a wider distribution compared to the diamond wire cutting method, posing a higher health risk to workers. PM measurement data did not exhibit a normal distribution, supported by the significant difference between the arithmetic mean and standard deviation. Due to the wide distribution, calculated $L_{eq(PM)}$ values were close to the upper limit of the data range. Therefore, the use of histogram analyses in addition to arithmetic means could yield more realistic and representative results. When PM measurement data were evaluated according to the arithmetic mean, the measured values were generally below the legislative limit values. Conventional regression methods were inadequate in estimating PM concentrations; instead, the M5P decision tree algorithm was successfully implemented, with correlation coefficients exceeding 0.88 in all tests. Ground vibration measurements conducted according to the TS ISO 2631-1 standard were below the limit values, while noise levels measured according to the TS EN ISO 9612 standard were mostly acceptable.

Keywords: *Decision Tree Algorithm, L_{eq}, $L_{EX\text{-}8h}$, M5P, PM_{10}, $PM_{2.5}$, PM_1, PM concentration, TSP.*

1. INTRODUCTION

Physical hazards (such as noise, vibration, dust and radiation) can cause tissue damage by transferring energy to individuals. Noise, vibration, and dust are highly effective in some occupational fields, including mining due to the nature of the work. Mining is among the sectors with the highest rates of occupational accidents [1]. Quarrying and other mining activities also rank fourth in occupational accidents within the mining sector [2]. Effectively preventing accidents occurring in mines is possible by conducting a thorough risk analysis and identifying and remediating environmental physical hazards. Activities such as block cutting, block tumbling, stacking, and transportation with heavy machinery are involved in natural stone quarries. Taking precautions against the hazards arising from these activities is essential by law. In the mining sector, which is a heavy and hazardous sector, machinery, labor, and technology are used jointly. As a result, the number and variety of required safety measures are increasing [3]. Özfırat et al. [4] identified three main triggering events through their risk analysis using an L-type matrix in natural stone processing plants and classified these events using the event tree method (ETA). They determined the probability of an accident due to lifting rope fatigue and rupture as 0.0025, diamond wire fatigue and rupture as 0.01, and a catastrophic accident probability due to electrical leakage as 0.0075. Risk classification has been addressed using different risk analysis methods in underground and aboveground facilities [5-7].

Vehicle noise from trucks, heavy machinery, and agricultural vehicles has both direct and indirect health effects. The impact on human health varies depending on factors such as the type and intensity of

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the noise, the duration of exposure, individual sensitivity, and general health status [8]. Long-term exposure to high levels of vehicle noise is associated with an increased risk of hearing loss, heart disease, and stroke [9]. Noise-induced hearing loss typically occurs when noise levels consistently exceed 85 dB(A) and personal protective equipment is not used or is used incorrectly. To ensure effective protection, not only the noise level but also the frequency content must be considered, as hearing protectors are generally designed for specific frequency spectrums and exhibit varying performance at different frequencies [10]. Duran et al. [11] measured the daily equivalent noise level at natural stone processing facilities in Sivas and the surrounding area and found that it was around or above the exposure limit value (87 dBA) specified in relevant regulations. Furthermore, considering the machinery and plant environment, the frequency ranges with the highest noise levels are mostly between 630 Hz and 5000 Hz, mostly around 3150 Hz. This suggests that workers in natural stone processing facilities may experience hearing-related health problems. However, a literature review reveals the lack of detailed studies on noise measurements in natural stone quarries. Noise exposure can not only cause permanent hearing loss but also have systemic health effects. Continuous exposure to high noise levels can contribute to the development of cardiovascular diseases such as increased heart rate, high blood pressure, and coronary heart disease. Staseva et al. [12] state that the increased use of noise and vibration, coupled with the increase in machinery and equipment used in the workplace, has harmful effects on the human body. Workers in natural stone mining are exposed to various types of vibration during their workplace activities. This exposure, which occurs while standing, sitting, or in some cases, in direct contact with the vibration source, can lead to long-term health problems. Health effects caused by vibration generally appear after several years of continuous exposure [13]. Worker exposure to vibration is related to the point of entry into the body [14]. Vibration exposure has become a hidden cause of occupational illness among workers in natural stone mining. Hand-arm vibration (HAV) is a common hazard for workers in many industries and occupations. Workplace exposure to HAV can result from the use of hand-held power tools (hammer drills), hand-guided machines (martop drills), and hand-fed machines (grinders). Long-term and regular exposure to this vibration can affect operator health. However, the risks associated with vibration can be controlled, and workers can be protected against the adverse effects caused by vibration. To protect workers and comply with vibration regulations, employers must assess the risks and plan how to control them [15].

Among factors related to the working environment in Poland, dust was identified as the most significant risk after noise [16]. Mocek and Mocek [17] emphasize that mining is the most affected by dust in industrial sectors. Anwer [18] evaluated air quality in areas with and without marble factories, assessing particulate matter concentrations in terms of total suspended particulate matter (TSP). The term "dust" is generally used for particles smaller than 75 μm that can remain suspended in the air for a certain period of time [19]. Dust is defined as substances with particle sizes ranging from 1 μm to 100 μm that are formed as a result of the drilling, crushing, transportation, abrasion, grinding, shredding, incineration, etc. of various inorganic and organic materials and that slowly settle under the influence of gravity [19], [20]. Particulate matter (PM) is defined as solid and liquid particles (aerosols) suspended in the air [21-23].

Marble forms when limestone undergoes changes caused by pressure and temperature. It is composed mainly of minerals such as calcite, magnesite, small amounts of hematite, and silica. In addition to the possibility of developing pneumoconiosis due to exposure to inorganic dust, cough, sputum production, and lung function deterioration can occur without developing pneumoconiosis. Although marble dust is an inert dust, it is known to cause silicosis because of its silica content. Research has shown that poor air quality causes various cardiovascular and respiratory diseases and is a leading factor in increased mortality rates. It has been determined that more than two million premature deaths occur each year due to air pollution [24].

Increasing anthropogenic activities, industrialization, and urbanization worldwide have intensified emissions of various pollutants that cause air pollution. Air pollution from dust generated during natural stone production can seriously affect the general physiological functions of humans and plants. It has been reported that workers in natural stone processing facilities experience cough and sputum more frequently

than office workers [25].

A study has shown that marble quarries and marble-based industries in Pakistan significantly increase air pollution. Dust generated during marble production and extraction adversely affects both plant physiology and human health. In addition, air quality was assessed in the Darmangi and Malagori districts where marble factories are located and in the areas where they are not. Total suspended particulate matter (TSP) levels were measured using an EPAM-5000 instrument, and the presence of $PM_{2.5}$ and PM_{10} particles in marble dust was analyzed using a spectrophotometer. The TSP concentration in the Darmangi and Malagori districts where marble factories are located was 626 μg/m³ and 5321 μg/m³, respectively. $PM_{2.5}$ and PM_{10} levels were measured as 189 μg/m³ - 520 μg/m³ (Darmangi) and 195 μg/m³ - 631 μg/m³ (Malagori), respectively. These values exceed World Health Organization (WHO) standards and reveal that areas where marble factories are located are more susceptible to air pollution. The study recommends moving marble factories away from residential areas, implementing environmental regulations, managing waste and controlling PM levels, and encouraging the use of protective equipment [24].

There are only a limited number of studies on the measurement of PM concentrations released during activities at natural stone quarries in our country. The mineralogical properties of natural stones extracted from different regions often differ. This affects the impact of any dust generated on respiratory function. In this study, PM, noise, and vibration values were measured during diamond wire cutting and monolamella activities at two different natural stone quarries in and around Sivas, and PM concentration data were modeled.

2. MATERIAL AND METHODS

PM, noise, and ground vibration measurements were carried out at two open-pit natural stone (travertine) quarries operating within the borders of Sivas Province. During the measurement process, PM, noise, and vibration data were recorded simultaneously, and measurement periods were set to be at least 10 minutes. This period is set to cover the full working cycle of diamond wire cutting and monolamella machines during the cutting process. Handheld PM and noise measurement devices are mounted on a tripod takeometer stand at a safe distance (2-10 m) from natural stone cutting machines. The devices are positioned at a height of 1.5-1.6 m from the ground, taking into account the breathing height of an adult (Figure 1).



Figure 1. PM and noise measurement in natural stone monolamella and wire cutting machines (a; monolamella machine b; diamond wire cutting machine)

During the measurement process, TSP, PM_{10}, $PM_{2.5}$, and PM_{1} concentration values were recorded simultaneously with the PM analyzer. The handheld device DUSTMATE, used for PM measurement, uses light scattering technology to determine the concentration of particles and dust in the air. The device can simultaneously measure TSP, PM_{10}, $PM_{2.5}$, and PM_{1} concentrations using a 1 mm stainless steel mesh laser nephelometer detector. Measurement data was transferred to a computer via PC-Link for analysis. The PM measuring device is capable of detecting dust and smoke sources at low concentrations down to 0.1

μg/m³ in the air. The device can measure particulate matter up to a level of 6000 μg/m³ (60 mg/m³ without size selection) with an air flow rate of 0.6 min/l and a sensitivity of 0.01 μg/m³. The measurement capacity covers particle diameters between 0.5 μm and 20 μm, classifying all particle materials above 20 μm as 20 μm [26-29]. Data was recorded at 10-second intervals using a PM measuring device and transferred to a computer using AirQ™ software. The data was organized using EXCEL™ software, and the resulting data was transferred to SPSS and WEKA software for analysis and modeling. The handheld DUSTMATE used for PM measurement is shown in Figure 2. This device measures in accordance with the CEN-TR 16013-3 standard.

As another stage of the study, noise and vibration were measured. Noise measurements conducted at natural stone quarries were carried out in accordance with the standards specified in the "Noise Regulation". The Svantek noise measurement device used in this context can perform measurements based on three different profiles according to A, C, and Z (linear) frequency weightings; it can report parameters such as SPL, L_{eq}, SEL, Lden, Ltm_3, Ltm_5, Ln (L1-L99), L_{Max}, L_{Min}, and LPeak (Figure 2). The device, with a dynamic measurement range of over 110 dB, has the capacity to measure noise levels ranging from 15 dBA RMS to 140 dBA Peak. In addition, long-term data recording is possible with MicroSD card support [30], [31]. Field studies were conducted based on the limits and action values defined in the "Regulation on the Protection of Workers from Noise-Related Risks" published in the Official Gazette dated 28.07.2013 and numbered 28721. In addition, noise exposure is determined in accordance with TS EN ISO 9612:2009 "Acoustics – Determination of Occupational Noise Exposure – Engineering Method" standard.

A six-channel analyzer was used for ground vibration measurement. The device meets the requirements specified in ISO 8041:2005, ISO 2631-1, ISO 2631-2, ISO 2631-5, and ISO 5349 standards. It is possible to set filters for whole-body vibration (Wd, Wk, Wm, Wb in accordance with ISO 2631-1) and hand-arm vibration (Wh in accordance with ISO 5349) on a channel-by-channel basis. The vibration measurement device can record TVT acceleration values between 0.01 m/s² KOK and 50 m/s² PEAK (Figure 2).



Figure 2. Measuring devices (a; PM meter b; Noise meter, c; Vibration analyzer).

3. MEASUREMENT RESULTS

Determining PM concentrations, noise, and vibration levels resulting from activities in natural stone quarries is crucial for understanding environmental impacts and assessing air quality. This study analyzed PM concentrations, noise, and vibration data measured during monolamella and diamond wire cutting operations in two open-pit natural stone quarries in Sivas province. The first section presents the results of particulate matter measurements, while the second section presents the results of noise and vibration measurements.

3.1 PM MEASUREMENT RESULTS

PM measurements include TSP, PM_{10}, $PM_{2.5}$, and PM_1 concentrations. The PM concentration data obtained showed a wide range of distribution (Table 1). During the monolamella process, TSP and PM_{10} concentrations ranged from 1.5 to 6527.9 μg/m³, depending on the operation, while during the diamond wire cutting process, they ranged from 1.5 to 5010.0 μg/m³. When evaluated in terms of smaller particles, $PM_{2.5}$ and PM_1 concentrations during the monolamella process ranged from 0.2 to 652.79 μg/m³, while during the diamond wire cutting process, they ranged from 0.18 to 392.18 μg/m³. The analyzed raw data sets do not conform to a normal distribution. Significant differences were observed between the calculated PM measurement values in terms of arithmetic mean and standard deviation. The large difference between the arithmetic mean and the standard deviation indicates that the data is scattered and heterogeneously distributed. The equivalent continuous PM concentration, Leq(PM), is defined as the representation of a variable PM concentration measured over a specific time period as an equivalent constant PM concentration. The accepted formula is presented in equation 1 [29]. Similarly, $L_{10(PM)}$, $L_{50(PM)}$, and $L_{90(PM)}$ represent the PM concentrations exceeded in 10%, 50%, and 90% of measurements, respectively.

$$Leq(PM) = 10 \cdot log_{10}\left[\frac{1}{N}\sum_{i=1}^{N}\left(10^{\left(\frac{PM_i}{10}\right)}\right)\right] \quad (1)$$

Here:
L_{eq}(PM), equivalent continuous cabin PM concentration,
PM_i, instantaneous PM concentration inside the cabin,
N, total number of measurements, expresses.

When PM concentrations fluctuate over a wide range, $L_{eq(PM)}$ and $L_{10(PM)}$ values tend to be close to each other. When PM concentrations vary within a narrow range, $L_{eq(PM)}$ and $L_{50(PM)}$ values are closer to each other. $L_{eq(PM)}$ plays an effective role in balancing multiple measurements because it is a logarithm-based calculation method. However, since the data set contains extremely large values, $L_{eq(PM)}$ tends to approach the upper limit due to the influence of these values. Therefore, in most cases, the $L_{eq(PM)}$ value is higher than $L_{10(PM)}$. Furthermore, there is no significant similarity between the arithmetic mean of the data and $L_{50(PM)}$. This situation reveals the heterogeneous nature of the measurement data and that the arithmetic mean may not fully reflect the actual distribution in the data set. In the evaluation of PM data, the respirable PM limit value (5 mg/m³) specified by the US Environmental Protection Agency for calcium carbonate (marble) dust was used, in accordance with the Dust Control Regulation published in the Official Gazette dated November 5, 2013, and numbered 28812 [32], [33]. Accordingly, when the arithmetic mean of the measurement data is evaluated, respirable PM in natural stone quarries is below the limit value (Table 1). On the other hand, due to the scattered nature of the data in this study, it is recommended that more reliable statistical indicators be preferred over arithmetic means in the analysis of PM concentrations. To this end, histograms of measurement data were generated and evaluations were made accordingly (Figure 3).

Looking at the histograms, for TSP concentrations during monolamella, 48.66% of the data from A natural stone quarry is below 2000 μg/m³, while 21.06% is above 5000 μg/m³. Although there was more data below 2000 μg/m³ in the B natural stone quarry (%50.52 - <2000 μg/m³), 23.35% of the measurements were at high concentrations. This shows that air pollution has intensified to certain levels in natural stone

quarries and that there are regional differences in PM concentrations. PM_{10} concentration intensity exhibits a distribution similar to TSP, with values above 5000 μg/m³ measured at 20.16% in A natural stone quarry and 22.70% in B natural stone quarry. $PM_{2.5}$ concentrations can cause chronic health problems because they can penetrate deeper into the body through the respiratory tract [34–42]. In A natural stone quarry, 54.27% of $PM_{2.5}$ is above 75 μg/m³, while in B natural stone quarry, this percentage is 53.89%. In the assessments conducted for PM_1 concentrations, high concentrations (>75 μg/m³) were detected at a rate of 45.3% in A natural stone quarry and 38.41% in B natural stone quarry. In general, when the measurement data was examined, it was observed that TSP and PM_{10} concentration data was higher at the B natural stone quarry above 5000 μg/m³, while $PM_{2.5}$ and PM_1 data was higher at the A natural stone quarry above 75 μg/m³. This situation indicates that coarse PM levels are high in A natural stone quarry, while fine PM levels are higher in B natural stone quarry.

Table 1. PM concentrations from diamond wire cutting and monolamella activities

Activity	PM concentration (μg/m³)	Mean ± SD	Min-Max (μg/m³)	$L_{eq(PM)}$ (μg/m³)	$L_{10(PM)}$ (μg/m³)	$L_{50(PM)}$ (μg/m³)	$L_{90(PM)}$ (μg/m³)
Monolamella (A firm)	TSP	2455.32 ± 2437.96	13.9 - 6527.9	6516.72	6133.38	1698.90	52.34
	PM_{10}	2290.35 ± 2351.11	12.8 - 6527.9	6516.72	6002.72	1384.90	27.22
	$PM_{2.5}$	220.99 ± 223.24	4.8 - 652.79	637.11	566.87	132.38	5.98
	PM_1	152.36 ± 192.52	1.0 – 652.79	637.09	478.94	28.57	1.19
Monolamella (B firm)	TSP	2620.92 ± 2478.41	2.9 - 6527.9	6519.03	6527.90	2013.55	7.15
	PM_{10}	2410.62 ± 2480.43	1.5 - 6527.9	6519.03	6527.90	1482.75	5.20
	$PM_{2.5}$	190.58 ± 210.92	0.8 - 652.79	637.24	549.04	104.05	1.30
	PM_1	127.86 ± 188.74	0.2 – 652.79	636.94	471.59	18.12	0.30
Diamond wire cutting (B firm)	TSP	443.33 ± 880.52	1.6 - 5010.0	4988.33	1830.22	37.60	4.40
	PM_{10}	325.67 ± 758.38	1.5 - 4840.3	4818.63	1287.08	13.80	3.24
	$PM_{2.5}$	32.32 ± 68.05	0.67 - 392.68	371.00	135.97	2.05	1.12
	PM_1	8.37 ± 20.27	0.18 - 109.47	89.23	26.83	0.43	0.27

In diamond wire cutting, the measured TSP concentration at the B natural stone quarry is between 1.6 and 5010 μg/m³. 89.1% of the measurement data was below 2000 μg/m³, while measurements above 5000 μg/m³, which is considered a high concentration area, remained at a low rate of 0.65%. PM_{10} concentrations were measured in the range of 1.5–4840.3 μg/m³, with 94.55% of the data concentrated below 2000 μg/m³. As a result, TSP and PM_{10} measurements generally concentrated below 2000 μg/m³, and measurements above 5000 μg/m³ were found to be quite low. Furthermore, the absence of any measurements above 5000 μg/m³ for PM_{10} indicates that this PM remained within a certain limit in terms of density. $PM_{2.5}$ concentrations ranged from 0.67 to 392.68 μg/m³, with 78.23% of the measured data below 25 μg/m³, indicating relatively low levels. In contrast, measured $PM_{2.5}$ values exceed 75 μg/m³ by 14.98%. PM_1 concentrations ranged from 0.18 to 109.47 μg/m³, with 88.43% of the data below 25 μg/m³ and 4.09% above 75 μg/m³.

The findings obtained when evaluating PM concentrations measurements during monolamella and diamond wire cutting activities at the B natural stone quarry are as follows. The concentrations of PM concentrations measured during monolamella vary over a wider range than those measured during diamond wire cutting, with particularly high concentrations of $PM_{2.5}$ and PM_1. It can be said that the fact that 53.90% of $PM_{2.5}$ occurs above 75 μg/m³ in the sieving process is critical data for assessing the potential effects of respirable fine particles on human health. When the distribution of PM_1 was examined, it was found that 38.32% of it occurred above 75 μg/m³. In diamond wire cutting, most of the $PM_{2.5}$ and PM_1 measurements are concentrated in low concentration ranges compared to monolamella. The fact that 4.09% of PM_1 occurs above 75 μg/m³ indicates that this activity produces relatively lower levels of fine PM. This situation shows that more small-diameter PMs are exposed in the monolamella process than in the diamond wire cutting process. When evaluated in terms of air quality and human health, it is possible

to say that monolamella operations pose a greater risk.

During diamond wire cutting, it is noteworthy that PM_{10} concentrations were largely below 2000 $\mu g/m^3$ and that no data measurements above 5000 $\mu g/m^3$ were recorded. This situation indicates that diamond wire cutting has lower high-concentration (5000 $\mu g/m^3$) PM concentrations than monolamella. It shows that PM concentrations released during natural stone production processes vary depending on the type of activity carried out under the same quarry conditions. As a result, the monolamella process exhibited a distribution containing more PM in the high concentration range, while the diamond wire cutting process exhibited a distribution with a lower PM density.

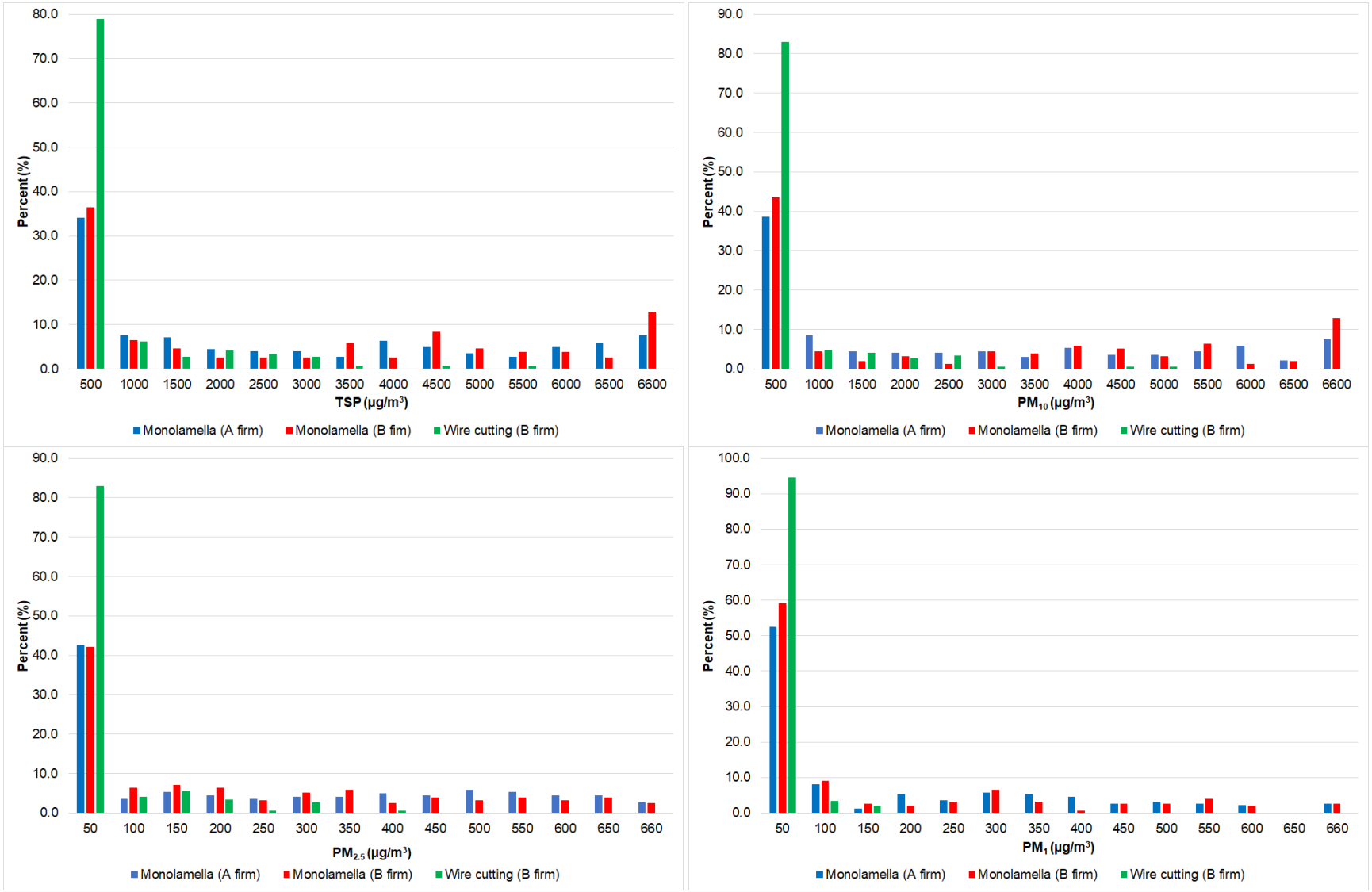


Figure 3. PM concentration histograms measured in natural stone quarries

3.2 NOISE AND VIBRATION MEASUREMENT RESULTS

Noise measurements were carried out in accordance with TS EN ISO 9612-2009 "Acoustics - Determination of Occupational Noise Exposure - Engineering Method"[43] . The measurement results were evaluated according to the limits and action values specified in the Regulation on the Protection of Workers from Noise-Related Risks, published in the Official Gazette dated 28.07.2013 and numbered 28721. To assess noise exposure levels, L_{max}, L_{min}, and L_{eq} values were measured, and the daily exposure value ($L_{EX\text{-}8h}$) normalized to an eight-hour reference period was calculated [31]. The ($L_{EX\text{-}8h}$) formula is presented in equation 2 [31]. The regulation specifies the limit values for noise exposure and the obligations that employers must fulfill if these values are exceeded. The regulation defines exposure action values and exposure limit values.;

- Lowest exposure action value (LEX, 8 hour) = 80 dB(A),
- Highest exposure action value (LEX, 8 hour) = 85 dB(A),
- Exposure limit value: (LEX, 8 hour) = 87 dB(A) is given in the form of.

$$Lex - 8h = Leq, T + 10Log(T/8) \quad (2)$$

Here:

L_{Ex}, daily exposure to noise at work

L_{eq}, equivalent continuous sound pressure level

T, shift duration (hours).

The assessment for the natural stone quarry was made according to the highest exposure action value, and the noise and vibration values measured and calculated from the monolamella and diamond wire cutting machines are given in Table 2. The data were analyzed by converting them into histogram graphs in Figures 4 and 5.

Workers in natural stone mining are exposed to vibration while standing, sitting, and in some cases while in contact with the vibration source. Health problems caused by vibration usually appear after several years of exposure to vibration [13]. Vibration measurements were performed using a ground-type vibration measurement device and analyzer. Vibration measurement records were calculated using the integrated environmental monitoring module [31], of the TVT analysis package used in the study. Vibration measurements were performed in accordance with ISO 2631-1 standard [44]. The measurement results provided in Table 2 have been interpreted in accordance with the exposure limit values and exposure action values specified in the "Regulation on the Protection of Workers from Vibration-Related Risks," published in the Official Gazette dated August 22, 2013, and numbered 28743. Accordingly, a vibration value below the exposure action value specified in the legislation for wire cutting and monolamella machines has been measured.

Risk assessment studies conducted at natural stone quarries and processing facilities indicate that noise, vibration, and dust measurements must be taken at regular intervals and that it is important to conduct detailed health checks on workers [45], [46]. In this context, our study, which was conducted using the risk assessment method developed by Reinhold and Tint [10] as a reference, determined the acceptable risk level for noise (TRL) <80 dB has been determined. Health parameters evaluated in terms of workers exposed to noise include fatigue, psychological stress, concentration disorders, decreased cognitive capacity, reflex muscle tension, tinnitus, and mild speech difficulties among the first-stage findings. These symptoms are usually early warning signs, but if the necessary measures are not taken, they can lead to more serious health problems. In the PM assessment, the reference value of 5 mg/m^3 for respirable PM limits set by the US Environmental Protection Agency in the "Dust Control Regulation" was used; concentrations below this value are considered an acceptable level of risk. A similar approach has been adopted in vibration measurements, and a value of <0.5 m/s^2 was set as the threshold. As a result, based on the measurements and analyses carried out, it was determined that noise, vibration, and PM levels remained within acceptable risk limits.

Table 2. Noise/vibration parameters measured and calculated from monolamella and diamond wire cutting machines

Company Name-Code	Machine	Measurement Period ss:dd:nn	Filter, detector	Ltepe (dB)	Lmax (dB)	Lmin (dB)	SPL (dB)	Leq (dB)	SEL (dB)	Lden (dBA)	Lt3 (dBA)	LTeq (dBA)	LEPD (dBA)	L_{ex8h}	ahw (m/s^2)	VDV ($m/s^{1,75}$)
A	Wire cutting	00:09:52	A, Hızlı	105.1	87.7	33.2	80.4	67.9	95.6	72.9	71.7	72.9	67.9	68.7	0.013	0.499
			C, Hızlı	105.1	92.1	47.3	82.0	72.5	100.2	77.5	75.8	76.9	72.5			
	Wire cutting	00:07:39	A, Hızlı	102.1	89.4	37.4	63.9	68.4	95.1	73.4	74.1	76.3	68.4	68.4	0.162	4.487
			C, Hızlı	102.1	91.9	51.3	74.4	76.5	103.1	81.5	80.0	81.3	76.5			
	Monolamella	00:17:08	A, Hızlı	97.3	79.3	33.1	56.6	60.9	91.0	65.9	68.0	69.3	60.9	60.9	0.006	0.074
			C, Hızlı	97.3	84.4	49.0	60.6	64.8	94.9	69.8	71.0	72.2	64.8			
	Monolamella	00:09:42	A, Hızlı	90.2	72.9	50.2	51.5	55.8	83.5	60.8	61.5	62.5	55.8	55.8	0.006	0.064
			C, Hızlı	90.2	76.9	57.8	59.3	62.1	89.8	67.1	65.6	66.3	62.1			
	Monolamella	00:14:36	A, Hızlı	97.1	78.3	41.9	46.9	65.0	94.5	65.0	67.0	67.7	65.0	50	0.158	3.485
			C, Hızlı	97.1	86.2	50.5	54.7	71.9	101.3	71.9	74.2	74.8	71.9			
B	Wire cutting	00:00:02	A, Hızlı	83.8	71.3	64.6	68.1	67.5	70.5	67.5	71.3	71.3	67.5	67.5	0.006	0.071
			C, Hızlı	83.8	70.1	64.1	67.3	66.6	69.6	66.6	70.1	70.1	66.6			
	Monolamella	00:15:00	A, Hızlı	99.0	75.5	55.0	60.3	63.3	92.8	63.3	66.4	66.8	63.3	63.3	0.006	0.065
			C, Hızlı	99.0	83.9	58.5	63.1	64.2	93.7	64.2	67.8	68.5	64.2			
	Wire cutting	00:07:45	A, Hızlı	101.9	81.2	58.0	59.0	65.9	92.5	65.9	71.3	72.5	65.9	65.9	0.006	0.061
			C, Hızlı	101.9	89.8	65.7	69.3	72.7	99.4	72.7	76.7	78.1	72.7			

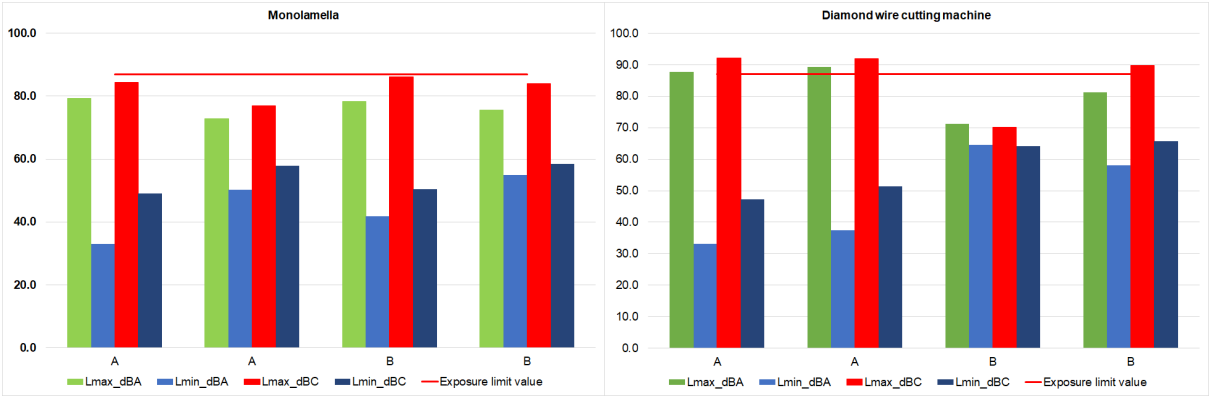


Figure 4. Natural stone quarries Lmax and Lmin noise measurement values

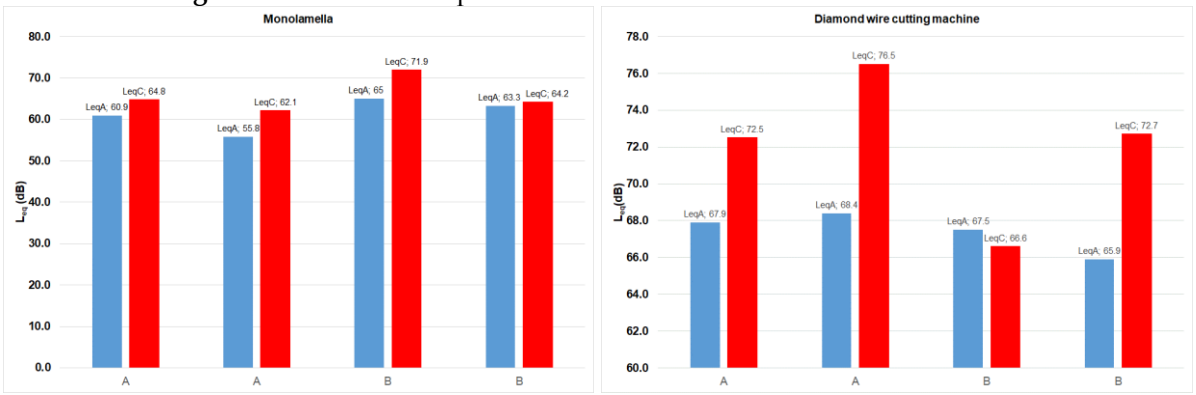


Figure 5. L_{eq} measurement values for natural stone quarries

4. MODELING of PARTICULATE MATTER MEASUREMENT DATA

The conformity of PM concentrations measured in natural stone quarries to a normal distribution was tested, and various analysis methods were examined for creating regression models. Since the data did not conform to a normal distribution, appropriate analysis methods were explored, and the WEKA M5P decision tree technique was identified as the most suitable. The M5P algorithm is a Java adaptation of the M5 algorithm developed by John Ross Quinlan on the WEKA platform [47]. The success of models created using decision tree algorithms is evaluated using various error metrics and performance indicators. These include the correlation coefficient (R), coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), relative absolute error (RAE), and root relative absolute error (RRSE). R^2 is a critical indicator that determines the accuracy rate of the model. When it approaches 0, the model does not match the data, and when it approaches 1, the model makes highly accurate predictions [48], [49]. Similarly, when the correlation coefficient (R) is high, the model's prediction performance improves; a value of 0.70 indicates high correlation [50], [51]. MAE and RMSE are basic error criteria that measure the magnitude of prediction errors. Low values increase the accuracy of the model, while RMSE is usually higher than MAE because it gives more weight to large errors [52]. MAE shows how close the estimates are to the actual values, while RMSE is used to analyze the variability in the error distribution [53]. Values close to zero indicate that the model performs well [54], [55]. M5P generates linear regression inequalities at the leaf nodes of the decision tree structure and performs node splitting based on the dependent variable using the inductive tree algorithm. The splitting process is stopped when the class value shows little difference or when the number of nodes decreases; then, pruning is applied to derive regression inequalities [56-61]. The M5P model contains two key numerical data points in its final leaves: one is the number of samples representing the leaf, and the other is the standard deviation as a percentage of the mean square error of the predictions. This second data point is calculated by dividing the mean square error of the linear model by the global absolute deviation [57], [50].

Considering the above criteria, the relationship between the dependent variable and independent

variables for estimating PM concentrations in diamond wire cutting and monolamella processes was tested using three different methods: training set, cross-validation, and percentage split. In the model construction procedure, both forward addition (FA) and backward elimination (BE) search approaches were applied. Figure 6 presents the model-building methods using the decision tree technique. In the training set method, all data were used for both training and testing. In the cross-validation method, the data set was divided into parts ranging from 5 to 15, depending on the size of the data set, and the model's accuracy was tested. The data were divided into parts, with one part used for testing and the remainder for training. This process was repeated by shifting all PM concentrations measured, so all data parts were used for both training and testing. In most models created, the best results were obtained when 10% of the data was used as test data and 90% as training data. In the percentage split method, the data set was divided into two parts at a specific ratio, with the first part used for training and the second for testing.In this method, the split was increased from 60% to 70% each time. In the splitting process, the best result, according to the criteria mentioned above, was achieved with a split of 66%. Here, a 66% split means that the first 66% of the set is used for training and the remaining 34% is used for testing.

In the models, the meta-learning algorithm, search technique selection, and the minimum number of samples allowed at each node are among the key decision factors that directly affect model performance. In the models, the minimum number of samples at each node was gradually increased starting from 1, and separate models were created for each parameter combination. In scenarios where no limit is imposed on the number of nodes, the model's generation of a large number of nodes can result in high correlation coefficients. However, the large number of rules and equations contained in such models makes it difficult to model PM concentrations in the real world in an applicable manner. Therefore, striking a balance between model complexity and explanatory power is critical in terms of both accuracy and practicality. The number of nodes generated by the models has also been used as a performance indicator. Since the MAE and RMSE indicators did not change significantly in the models developed using the M5P algorithm, the correlation coefficient and number of nodes of the models were used as performance criteria. According to the results of the modeling studies, it was observed that the interaction coefficients of all three methods were close to each other.

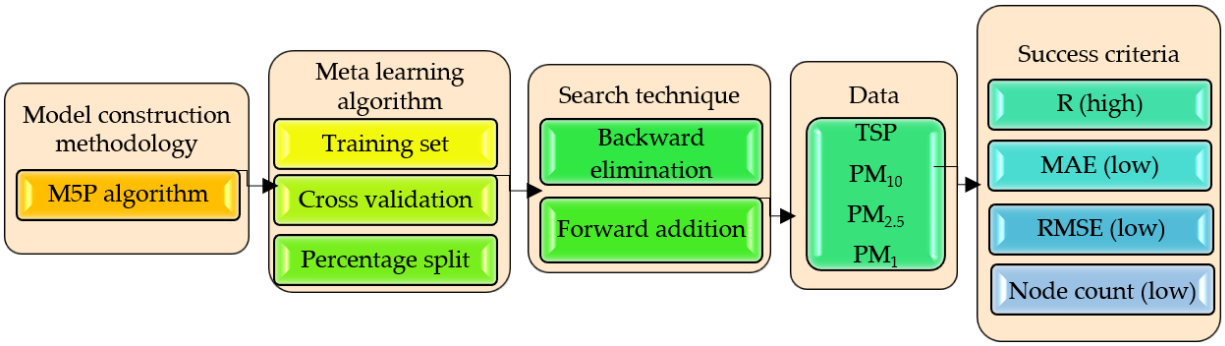


Figure 6. Modeling methodology used in the study

The regression analysis results between PM fluctuations calculated using the M5P decision tree algorithm are given in Table 3. According to the regression analyses performed, it was observed that the interaction coefficients were above 0.88 in all models, thus demonstrating that the models exhibited a high level of correlation and therefore performed better. For example, the actual and estimated PM_{10} concentration values for the monolamella activity are shown in Figure 6.

Table 3. Regression analysis results of PM concentration data from natural stone open pits using the decision tree algorithm

Machine	Test Method	Evaluation criterion	TSP	PM_{10}	$PM_{2.5}$	PM_1
Diamond wire cutting	Training set	Correlation coefficient	0.9898	0.9909	0.9598	0.9259
		MAE	71.1122	43.6197	7.8302	2.8364
		RMSE	125.0246	101.7248	19.0333	7.6334
		RAE (%)	11.8966	9.2114	17.4762	23.5791
		RRSE (%)	14.2474	13.4592	28.0616	37.7749
		Number of nodes	2	4	2	1
	Cross validation	Correlation coefficient	0.9834	0.9802	0.9564	0.9115
		MAE	82.2358	82.6445	7.8191	3.1228
		RMSE	137.2087	149.8744	19.8529	8.3354
		RAE (%)	17.3662	17.3958	17.3475	25.8342
		RRSE (%)	18.1541	19.7345	29.1252	41.0537
		Number of nodes	2	4	2	1
	Percentage split	Correlation coefficient	0.9958	0.9941	0.9778	0.8894
		MAE	115.4795	115.3499	8.3952	6.3135
		RMSE	249.4461	269.8089	21.3428	15.3576
		RAE (%)	16.2555	19.492	17.2775	49.3374
		RRSE (%)	20.9553	24.3466	24.6633	63.2696
		Number of nodes	2	4	2	1
Monolamella	Training set	Correlation coefficient	0.9975	0.9978	0.9877	0.9767
		MAE	113.537	104.3126	20.8452	24.0136
		RMSE	168.8159	158.7461	34.0784	40.9895
		RAE (%)	5.2371	4.8306	10.801	15.0065
		RRSE (%)	7.0427	6.617	15.6153	21.4822
		Number of nodes	3	2	3	4
	Crossvalidation	Correlation coefficient	0.9974	0.9977	0.9875	0.9707
		MAE	117.6413	107.3736	21.0259	26.7936
		RMSE	173.3206	164.3103	34.4412	45.8957
		RAE (%)	5.4246	4.9706	10.891	16.7348
		RRSE (%)	7.2275	6.846	15.7746	24.0378
		Number of nodes	3	2	3	4
	Percentage split	Correlation coefficient	0.9972	0.9974	0.9856	0.9711
		MAE	120.6113	110.8782	24.2973	27.8251
		RMSE	189.5038	181.2189	37.5653	46.7489
		RAE (%)	5.3494	4.9131	12.4108	17.1073
		RRSE (%)	7.642	7.2711	16.9505	23.9498
		Number of nodes	3	2	3	4

MAE; mean absolute error RMSE; root mean square error
RAE (%) relative absolute error RRSE (%); root relative absolute error

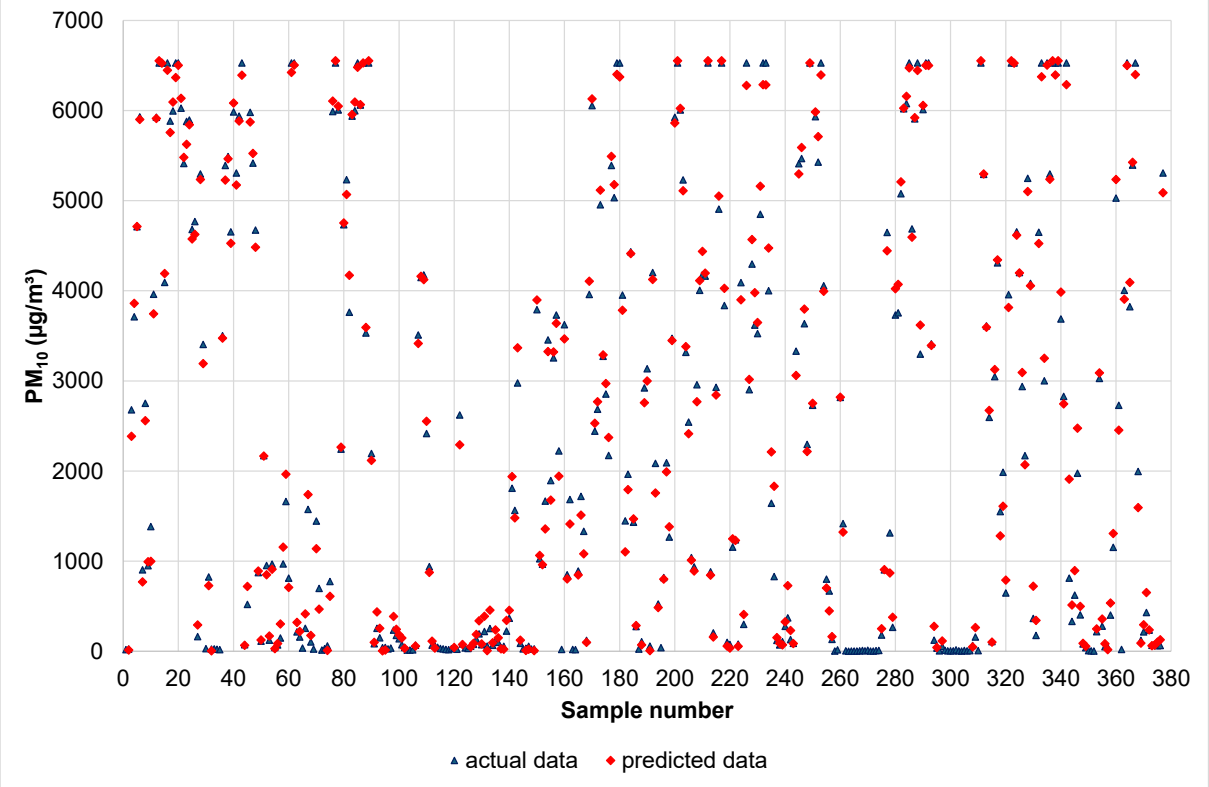


Figure 6. PM_{10} actual and predicted concentrations from the monolamella activity

The estimation rules and prediction equations of the models created to predict other PM types using a decision tree that encompasses PM concentrations are given in Table 4. In the analyses, decision tree studies conducted on different PM data sets revealed the determining factors affecting oscillation. In decision tree analyses performed for the TSP data set, two oscillation estimation equations were derived for diamond wire cutting, and three oscillation estimation equations were derived for monolamella. It was determined that PM_{10} was the decisive parameter in both models, but that $PM_{2.5}$ and PM_1 had no significant effect on the model. TSP's prediction shows that PM_{10} concentrations play an important role, whereas smaller PM sizes are not decisive in this modeling process. In decision tree analyses performed for the PM_{10} data set, four oscillation estimation equations were obtained for diamond wire cutting, and two oscillation estimation equations were obtained for monolamella. TSP was found to be the determining parameter in both models. In decision tree analyses performed for the $PM_{2.5}$ data set, two oscillation estimation equations were derived for diamond wire cutting, and three oscillation estimation equations were derived for monolamella. It was observed that PM_1 was the determining parameter in both models, and therefore it was understood that the distribution of $PM_{2.5}$ was largely shaped by the effect of PM_1. In the analyses performed on the PM_1 data set, one oscillation estimation equation was derived for the diamond wire cutting process and four oscillation estimation equations were derived for the monolamella process. No decisive parameter was found to predict PM_1 concentrations in diamond wire cutting, but $PM_{2.5}$ was found to be a decisive parameter in monolamella. This indicates that the concentration of PM_1 in the monolamella process is affected by $PM_{2.5}$. Decision tree analyses were used to systematically classify the determining factors in PM concentration processes and demonstrate that PM concentrations occurring during similar activities at different mines could be optimized through modeling. Decision tree models, make it possible to better understand the relationships between different types of PM and their oscillation mechanisms. These findings provide important information for air pollution management, optimization of industrial processes, and development of PM control strategies. Through the decision tree models developed, it has been determined which types of particulate matter are decisive and how components that do not contribute meaningfully to the process can be separated. In addition, the use of machine

learning techniques such as decision trees provides valuable information for predicting PM fluctuations and strengthening decision support mechanisms.

Table 4. Estimation rules and prediction equations for estimating PM concentrations in diamond wire cutting and monolamella operations

Activity	Model	PM	Oscillation estimation rules	Oscillation prediction equations
Diamond wire cutting	LM1	TSP	$PM_{10} \leq 71.55$	$0.1502 * PM_{10} + 34.0061$
	LM2		$PM_{10} > 71.55$	$1.0647 * PM_{10} + 236.8045$
	LM1	PM_{10}	$TSP \leq 47.8$	$0.1457 * TSP + 0.3991$
	LM2		$125.2 \geq TSP > 47.8$	$0.2753 * TSP + 13.1557$
	LM3		$522.8 \geq TSP > 125.2$	$0.2727 * TSP + 37.0872$
	LM4		$TSP > 522.8$	$0.9519 * TSP - 300.8052$
	LM1	$PM_{2.5}$	$PM_1 \leq 1.83$	$0.0041 * PM_{10} + 0.2793 * PM_1 + 2.4073$
	LM2		$PM_1 > 1.83$	$0.031 * PM_{10} + 2.1053 * PM_1 + 13.8833$
	LM1	PM_1	---	$-0.0055 * TSP + 0.3337 * PM_{2.5} + 0.0147$
Monolamella	LM1	TSP	$PM_{10} \leq 122.9$	$0.2041 * PM_{10} + 99.1387$
	LM2		$1569.55 \geq PM_{10} > 122.9$	$1.2001 * PM_{10} + 292.1776$
	LM3		$PM_{10} > 1569.55$	$0.9278 * PM_{10} + 529.0803$
	LM1	PM_{10}	$TSP \leq 1724.45$	$0.6864 * TSP + 2.8891 * PM_1 - 48.7556$
	LM2		$TSP > 1724.45$	$1.04 * TSP + 0.4467 * PM_1 - 526.8894$
	LM1	$PM_{2.5}$	$PM_1 \leq 14.075$	$0.003 * TSP + 5.4071 * PM_1 + 1.0654$
	LM2		$223.355 \geq PM_1 > 14.075$	$0.0242 * TSP + 0.997 * PM_1 + 53.2872$
	LM3		$PM_1 > 223.355$	$0.0356 * TSP + 0.4919 * PM_1 + 113.9153$
	LM1	PM_1	$PM_{2.5} \leq 96.95$	$-0.0019 * TSP + 0.0839 * PM_{2.5} + 1.2186$
	LM2		$337.66 \geq PM_{2.5} > 96.95$	$-0.0168 * TSP + 0.7816 * PM_{2.5} - 20.4607$
	LM3		$533.79 \geq PM_{2.5} > 337.66$	$-0.0031 * TSP + 0.783 * PM_{2.5} - 15.9527$
	LM4		$PM_{2.5} > 533.79$	$-0.0031 * TSP + 1.6049 * PM_{2.5} - 426.7321$

5. LIMITATIONS

The measurements in this study were performed using diamond wire cutting and monolamella machines. This choice was primarily due to the widespread use of these two machine types in natural stone quarries in the Sivas region, which limited access to other machine types.

A PM meter was used to monitor particulate matter (PM) emissions. However, to estimate PM concentrations with higher accuracy, it is recommended to integrate additional measurement devices and perform multiple measurements by positioning PM meters at different locations. This approach will significantly improve the reliability and representativeness of the modeling process by increasing data diversity.

The TSP, PM_{10}, $PM_{2.5}$, and PM_1 concentrations released during diamond wire cutting and monolamella operations show a very wide distribution. This makes it difficult to predict PM emissions accurately using a single regression equation based on other emission variables with conventional regression methods. Therefore, alternative modeling techniques are essential when classical regression approaches are inadequate. Decision tree-based modeling methods are gaining prominence in this context. In particular, the M5P algorithm provides flexible, explainable, and satisfactory results in estimating PM data with a wide distribution. M5P-based models can produce both reliable and interpretable estimates based on field data. These features make them a powerful tool for predicting PM concentrations in similar mining projects. For successful modeling, it is crucial that the prediction equations derived from the M5P algorithm are presented to decision-makers in a clear, understandable, and scientifically sound manner. Further scientific studies based on the M5P decision tree algorithm are necessary to predict PM concentrations in natural stone quarries with high accuracy. According to the existing literature, no alternative modeling method is more effective than the M5P algorithm for such datasets.

6. RESULTS

It was determined that PM concentrations (TSP, PM_{10}, $PM_{2.5}$, and PM_1) released during the monolamella process have a wider distribution than those from the diamond wire cutting process. This indicates that PM concentrations generated during the monolamella process may increase health risks for workers, and these risks may be more serious than those associated with diamond wire cutting.

PM measurement data do not follow a normal distribution and exhibit a highly scattered patern. The significant difference between the arithmetic mean and the standard deviation further indicates that the data do not meet the assumption of normality. Additionally, due to the wide distribution, the calculated Leq(PM) values were close to the upper limit of the data range. Therefore, in addition to arithmetic means, using histogram analyses to evaluate the data was found to be more appropriate for obtaining more realistic and representative results.

Analyses conducted according to Turkey's Dust Control Regulation and EPA standards showed that measured PM concentrations were generally below the respirable limit values. During the monolamella process, 53.90% of $PM_{2.5}$ and 38.32% of PM_1 measurements exceeded 75 $\mu g/m^3$, reaching levels that could pose a health risk. In contrast, during diamond wire cutting, PM_{10} values largely remained below 2000 $\mu g/m^3$, with no measurements above 5000 $\mu g/m^3$. This demonstrates that diamond wire cutting produces lower PM concentrations.

Because the PM data do not follow a normal distribution, classical regression methods were insufficient; instead, the M5P decision tree algorithm was successfully applied. The correlation coefficient (R) of the models tested with the training set, cross-validation, and percentage division was above 0.88 in all methods. Modeling revealed different predictor variables for each PM type, which varied according to the process type. The resulting prediction rules show that unmeasured PM types can be reliably predicted using measurable data, reducing the frequency of field measurements and measurement costs.

Values for acceleration and vibration dose remained below the limits; vibration transmitted from the ground to the feet was determined not to pose a significant health risk. These values were also calculated to be below the exposure action values specified in the Vibration Regulation. Noise levels during diamond wire cutting and monolamella processes were evaluated separately for each machine. At the A Natural Stone quarry, LeqA was measured at 55–60 dB and LeqC at 62–65 dB on the monolamella machine; at the B Natural Stone quarry, LeqA was measured at 65 dB and LeqC at 64–71 dB. These values are below the exposure action and limit values specified in the relevant legislation. For the diamond wire cutting machine, LeqA was measured at 68–77 dB at quarry A and 66–68 dB at quarry B, while LeqC was measured at 67–73 dB. Although the wire cutting machine produces higher noise levels than the monolamella machine, both machines remained below the limit values. However, the diamond wire cutting machine occasionally exceeded the dBC value of 85 dB. The study by Arıtan and Tümer supports the noise results [62]. When conducting risk assessments, more attention should be paid to vibration and thermal comfort conditions, which are physical risk factors that are often overlooked [63]. The negative effects of noise, PM and vibration have been investigated for underground mines [7]. Many studies have emphasized that physical risk factors are high in mines and that measures should be taken to reduce occupational accidents [6-64-65].

7. RECOMMENDATIONS

In particular, because of the $PM_{2.5}$ and PM_1 emissions released during the monolamella process, workers must use dust masks and respiratory protective equipment. When analyzing PM emissions, evaluating the data using the arithmetic mean and histograms instead of $L_{eq(PM)}$ may yield more reliable results. In this context, PM measurements inside the mines should be conducted regularly to continuously monitor air quality and ensure a safe working environment for workers. Open-source software such as WEKA enables the creation of low-cost and effective decision support systems for estimating and managing PM emissions; the widespread use of such software can support field engineers' technical decision-making processes. Measurements taken for monolamella and wire cutting machines showed differences in noise and PM values: while the noise value was high in one machine, the PM value was

higher in the other. Therefore, repeating measurements in quarries with different mineralogical characteristics will provide more accurate and clear results. As stated in the study by Ağca [46], it is very important to perform measurements related to noise, dust, and vibration in marble quarries.

Declaration of Ethical Standards

The authors declare to comply with all ethical guidelines, including authorship, citation, data reporting, and original research publication.

Credit Authorship Contribution Statement

Zekeriya Duran, Tuğba Doğan and Mehmet Genç envisioned and planned the research project. Zekeriya Duran and Tuğba Doğan carried out the material preparation and data gathering tasks. Zekeriya Duran and Tuğba Doğan conducted the statistical analyses. Zekeriya Duran, Tuğba Doğan and Mehmet Genç all contributed to the preparation of the article format. All authors commented on the final form of the manuscript.

Declaration of Competing Interest

The authors declare that there are no declarations of interest.

Data Availability

The data obtained from this study are available from the corresponding author upon reasonable request.

Funding / Acknowledgements

This work was supported by the Scientific Research Project Fund of Sivas Cumhuriyet University under Grant [M-2024-865].

Use of Artificial Intelligence

The authors confirm that no generative AI or AI-assisted technologies were used in the writing of this manuscript or in the production of the data/images presented.

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